



Complex Networks/ Foundations of Information Systems

6 March 2013

Robert J. Bonneau, Ph.D.
Division Chief
AFOSR/RTC



Integrity ★ Service ★ Excellence

Report Documentation Page

Form Approved
OMB No. 0704-0188

Public reporting burden for the collection of information is estimated to average 1 hour per response, including the time for reviewing instructions, searching existing data sources, gathering and maintaining the data needed, and completing and reviewing the collection of information. Send comments regarding this burden estimate or any other aspect of this collection of information, including suggestions for reducing this burden, to Washington Headquarters Services, Directorate for Information Operations and Reports, 1215 Jefferson Davis Highway, Suite 1204, Arlington VA 22202-4302. Respondents should be aware that notwithstanding any other provision of law, no person shall be subject to a penalty for failing to comply with a collection of information if it does not display a currently valid OMB control number.

1. REPORT DATE 06 MAR 2013		2. REPORT TYPE		3. DATES COVERED 00-00-2013 to 00-00-2013	
4. TITLE AND SUBTITLE Complex Networks/Foundations of Information Systems				5a. CONTRACT NUMBER	
				5b. GRANT NUMBER	
				5c. PROGRAM ELEMENT NUMBER	
6. AUTHOR(S)				5d. PROJECT NUMBER	
				5e. TASK NUMBER	
				5f. WORK UNIT NUMBER	
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) Air Force Office of Scientific Research ,AFOSR/RTC,875 N. Randolph,Arlington,VA,22203				8. PERFORMING ORGANIZATION REPORT NUMBER	
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)				10. SPONSOR/MONITOR'S ACRONYM(S)	
				11. SPONSOR/MONITOR'S REPORT NUMBER(S)	
12. DISTRIBUTION/AVAILABILITY STATEMENT Approved for public release; distribution unlimited					
13. SUPPLEMENTARY NOTES Presented at the AFOSR Spring Review 2013, 4-8 March, Arlington, VA.					
14. ABSTRACT					
15. SUBJECT TERMS					
16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT Same as Report (SAR)	18. NUMBER OF PAGES 29	19a. NAME OF RESPONSIBLE PERSON
a. REPORT unclassified	b. ABSTRACT unclassified	c. THIS PAGE unclassified			



2013 Spring Review



NAME: Complex Networks/Foundations of Information Systems

BRIEF DESCRIPTION OF PORTFOLIO:

Complex Networks and Foundations of Information Systems uses measured information to assure, manage, predict, and design distributed networks, systems, and architectures

LIST SUB-AREAS IN PORTFOLIO:

- *Local Network Research:* Guarantee and assure information transmission
- *Network Management Research:* Network and system protocols for resilient and robust
- *Global Network Research:* Mathematically represent network performance and design robustness
- *Foundations of Information Systems Research:* Measure, predict, and verify information system properties



Complex Networks & Foundations of Information Systems



Goals:

- **Measure system performance and calculate risk**
- **Preserve critical information structure and minimize latency over a heterogeneous distributed network and system**
- **Ensure network and system robustness and resilience under a diverse set of resource *constraints* and manage using dynamic models**
- **Represent global properties of a networked system in a unified mathematical framework for architecture and design**
- **Assess and Predict heterogeneous distributed systems performance using unified mathematical framework**

Foundations Goals

Complex Networks Goals



Complex Networks & Foundations of Information Systems



Payoffs:

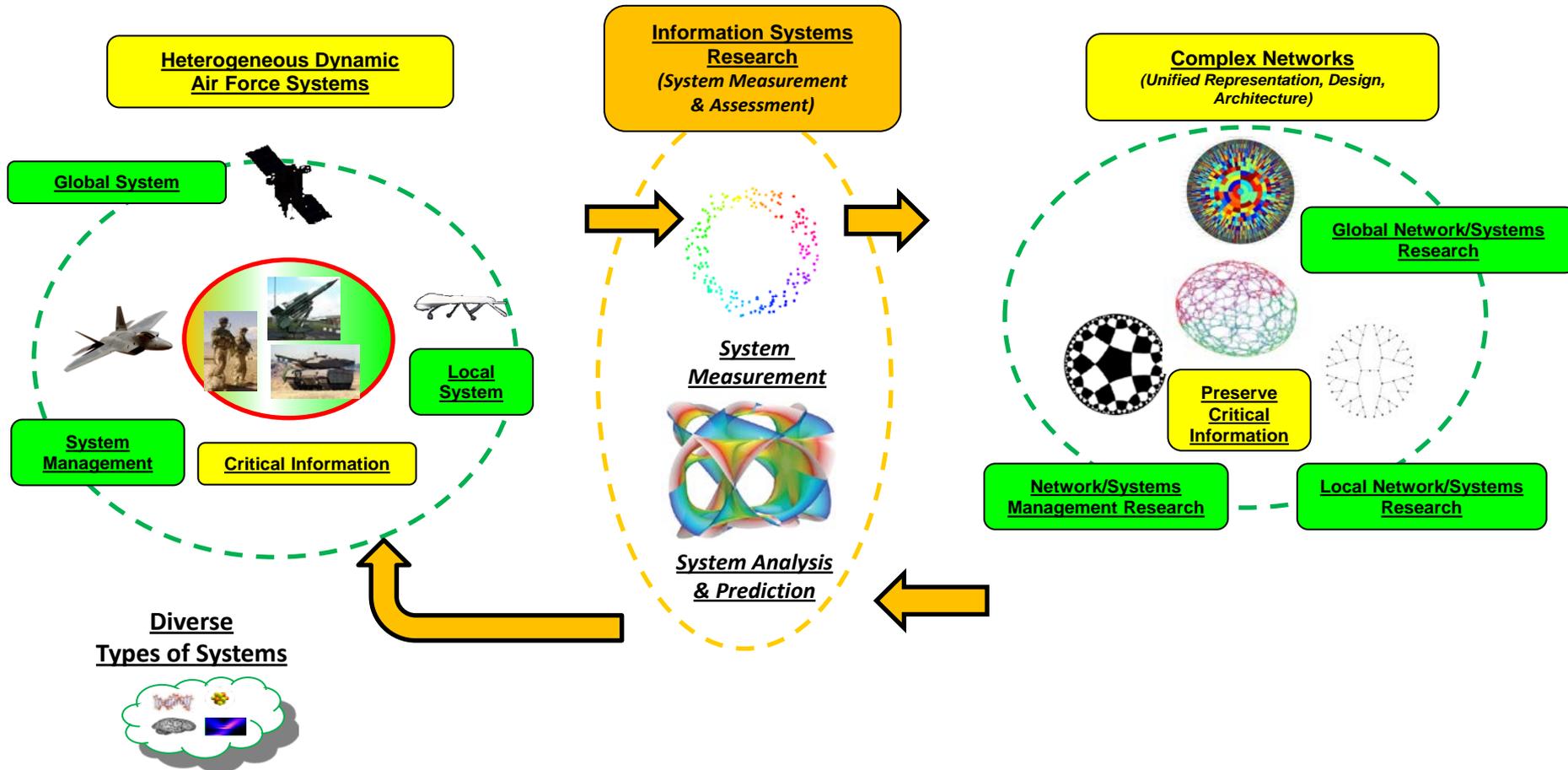
- **Preserve critical information structure in a network rather than just delivering packets or bits**
- **Quantify likelihood of a given network management policy to support critical mission functions**
- **Predict and manage network and system failure comprehensively**
- **Assess and verify properties of a distributed heterogeneous system where there is limited access to its elements**
- **Assess dynamic Air Force system mission performance and assess risk of failure**



Complex Networks and Information Systems Roadmap



Complex Networks and Information Systems uses measured information to assure, manage, predict, and design distributed networks, systems, and architectures



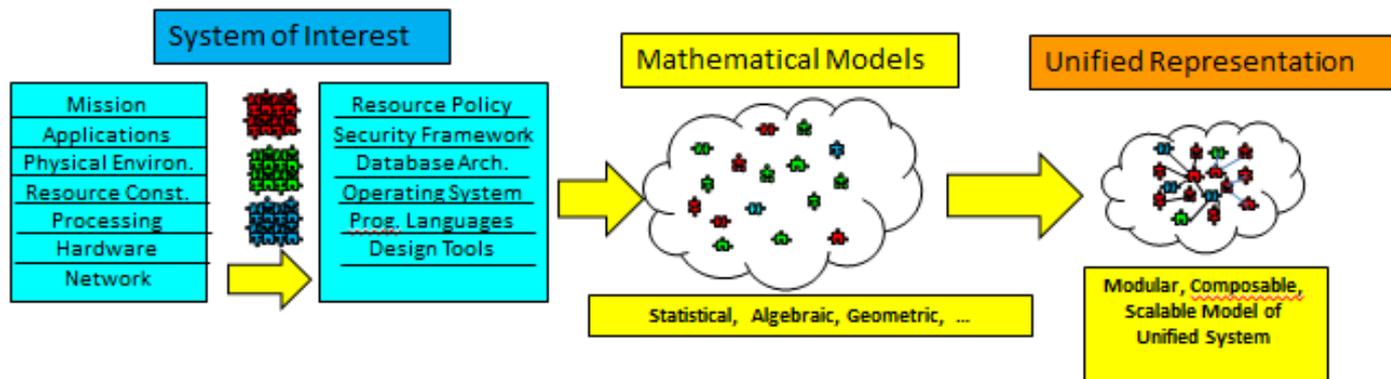


Information Systems Measurement

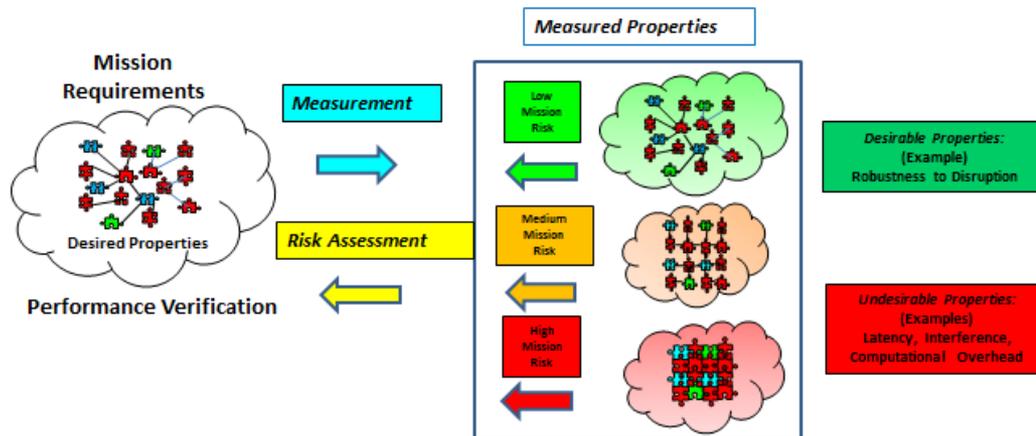


We wish to understand what and how to measure systems for representations that are traceable to mission performance and have quantifiable risk

What to measure?



How to measure?





Accurate Measurement of Systems Graph Parameters

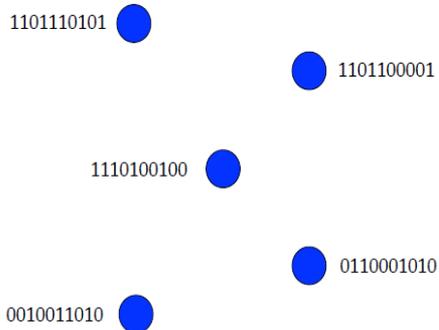


Dan Spielman, Yale

Approach: There are many different ways to represent networked systems. There needs to be a principled way of selecting the best inputs for geometric models to parameterize system performance.

Payoff: Systems can be parameterized in such a way as to minimize computational overhead and inaccuracies in model prediction using sparse geometric graph theory.

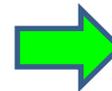
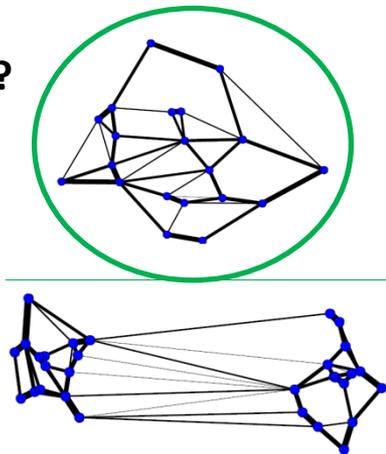
Critical Systems Information



Best Model?



Sparse Regression of Graph To Build Best Geometric Model



Best System Parameterization

$$\sum_{i=1}^n d_i \left\| \mathbf{x}_i - \frac{1}{d_i} \sum_{j \sim i} w_{i,j} \mathbf{x}_j \right\|^2$$

$$= \sum_{i=1}^n \left\| d_i \mathbf{x}_i - \sum_{j \sim i} w_{i,j} \mathbf{x}_j \right\|^2$$

Subject to $d_i \geq 1, \forall i$

MacArthur Genius Award Winner 2012



Statistical System

Estimation and Risk Analysis

Eric Kolaczyk, Boston University



Approach: Sample large systems guided by understanding of geometric invariants and risk analysis in how measurements were constructed.

Payoff: Minimum risk can be incurred from measurements of large system while still sampling in most computationally efficient way.

Minimum Risk Outcome for Graph Sampling

The Underlying Network-Graph $G = (V, E)$	The Inferred Network-Graph $\hat{G} = (V, \hat{E})$
Underlying Graph Characteristic $\eta(G)$	Inferred Graph Characteristic $\eta(\hat{G})$

- Let G be a connected, undirected binary graph
- Express the relationship between $G = G_{true}$ and $\hat{G} = G_{observed}$, in terms of their $n \times n$ adjacency matrices, as

$$W_{observed} = W_{true} + W_{noise}$$

where W_{noise} captures Type I and Type II errors.

- Our Goal:** Construct an estimator \hat{W} of W_{true} from $W_{observed}$ for which

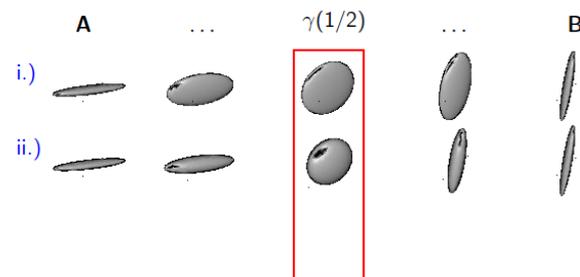
$$\|f(\hat{W}) - f(W_{true})\| \ll \|f(W_{observed}) - f(W_{true})\|$$

for any smooth statistic $f(W)$.

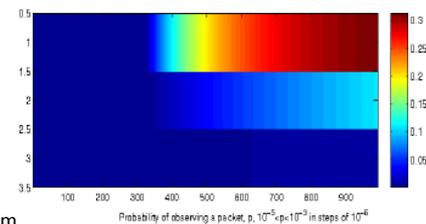
Geometric Strategies for Sampling Graph

Matrix Geodesics ($\alpha \in [0, 1]$)

- Euclidean geodesic: $\gamma(\alpha) = \alpha A + (\alpha - 1)B$.
- Log-Euclidean geodesic: $\gamma(\alpha) = \exp(\alpha A + (1 - \alpha)B)$.



Risk Performance Peer to Peer Network Data

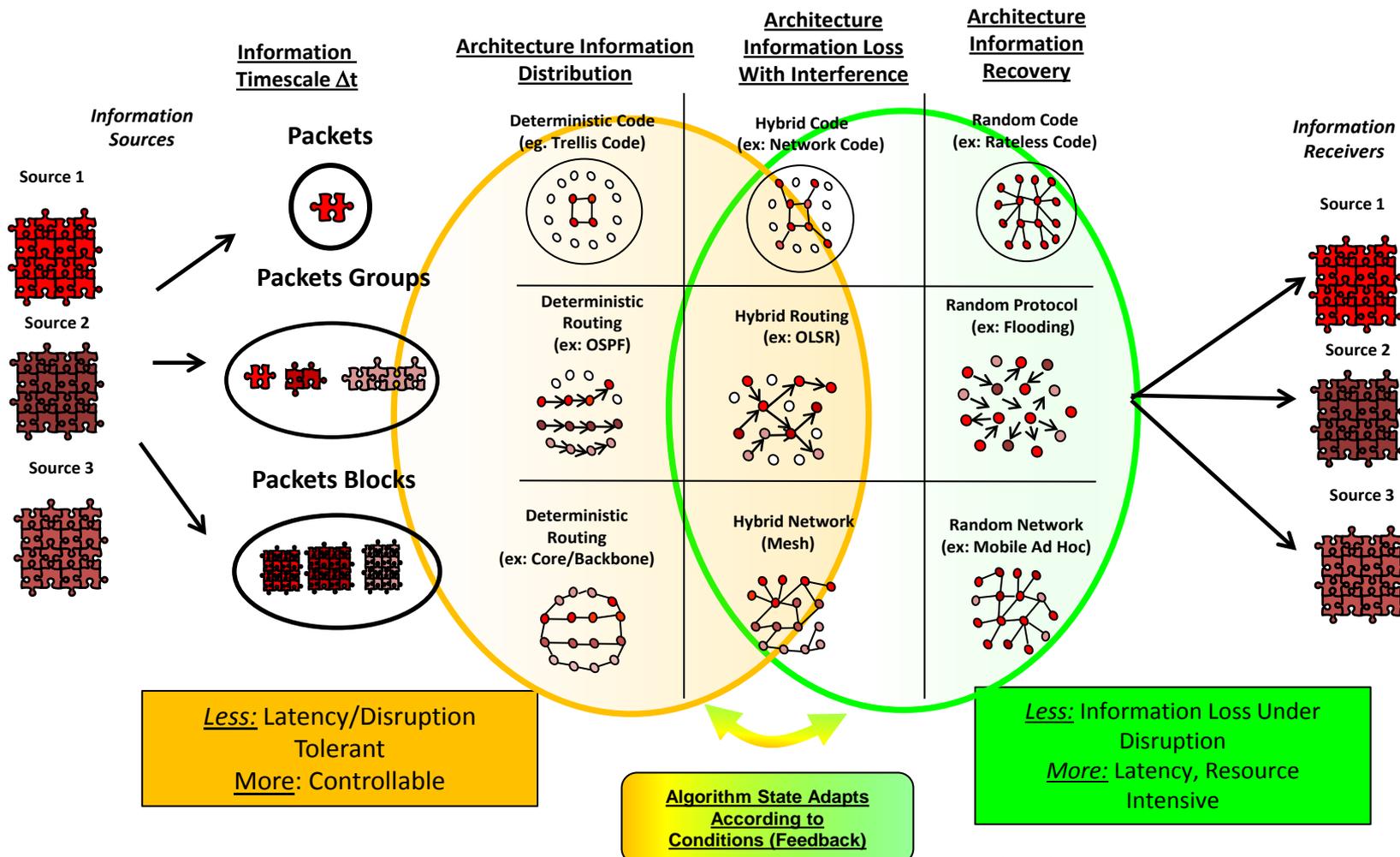




Complex Networks System Representation



- We wish to characterize network and system performance from measurement and develop coding, protocol, and architectures that adapt according to network/system state





Network Taxonomy



Narayan, Sanjeev UC Santa Cruz/Lucent

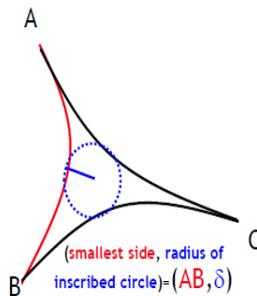
Approach: Develop a taxonomy of network properties through curvature and timescale invariants from hyperbolic geometry

Payoff: Space of network models can be developed and design principles and analysis algorithms derived to predict network behavior

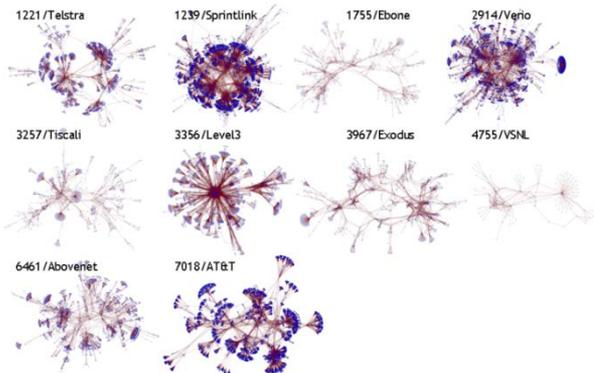
Geometric Curvature Invariant

1. 3-point "Triangle test" - Are triangles universally δ -thin?

- Select triangles
- For each triangle note shortest side L and computed the δ
- Counted number of such triangles, indexed by δ and L



Taxonomy of Physical Architecture Across Networks



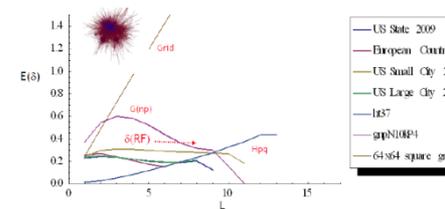
Characterization of Network Stack Across Layers (curvature connected to congestions)



Curvature vs. Timescale and Network Layer

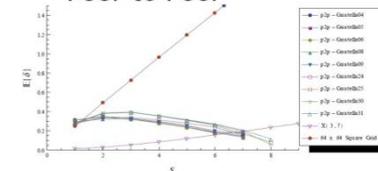
Application

Social Network



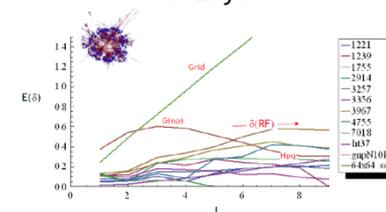
Protocol

Peer to Peer



Architecture

IP Layer





Entropy Classes for Dynamic Network Models

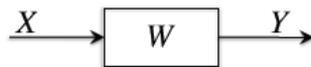
Lizhong Zheng, MIT



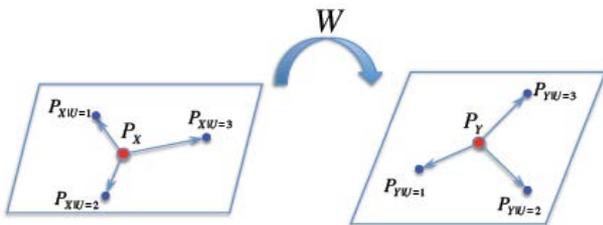
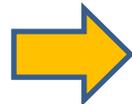
Approach: Deriving models for network protocol analysis has assumed fixed protocols without the benefit of feedback or dynamic correlations in coding and protocol. Using Renyi correlation analysis and entropy to model this wider class of models allows greater flexibility in describing statistical classes.

Payoff: Complex phenomena such as feedback in coding can be modeled under dynamic heterogeneous conditions.

Network Channel Architecture Feedback Channel & Geometric Invariants



$$P_{X|U=u} = P_X + \epsilon \cdot [\sqrt{P_X}] \cdot L_u$$



Renyi Channel Correlation Analysis (connected to geometric curvature)

- Maximal correlation, a measure of dependence:

$$\rho(X, Y) \triangleq \sup_{f(X), g(Y): E[f]=E[g]=0, E[f^2]=E[g^2]=1} E[f(X)g(Y)]$$

- Conditional Expectation Operator: $B : \mathcal{F}_Y \mapsto \mathcal{F}_X$

$$B(f) = E[f(X)|Y]$$

- Renyi

$$\rho(X, Y) = \sup_f \frac{E[(B^\dagger B(f))^2]}{E[f^2]}$$



Feedback in Coding Theory

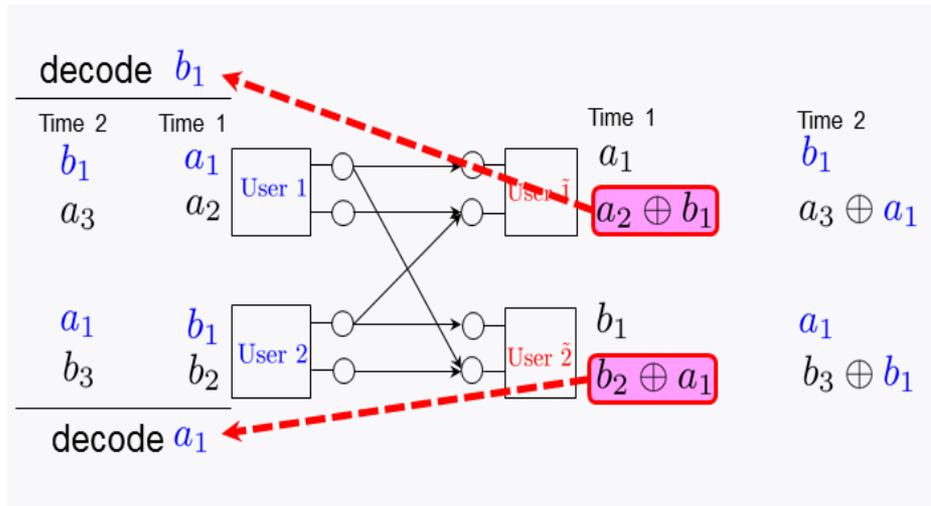


D. Tse, Berkeley, P. Gupta, Alcatel Lucent, D. Shah, MIT

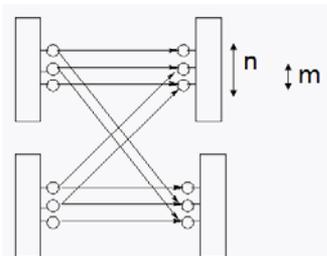
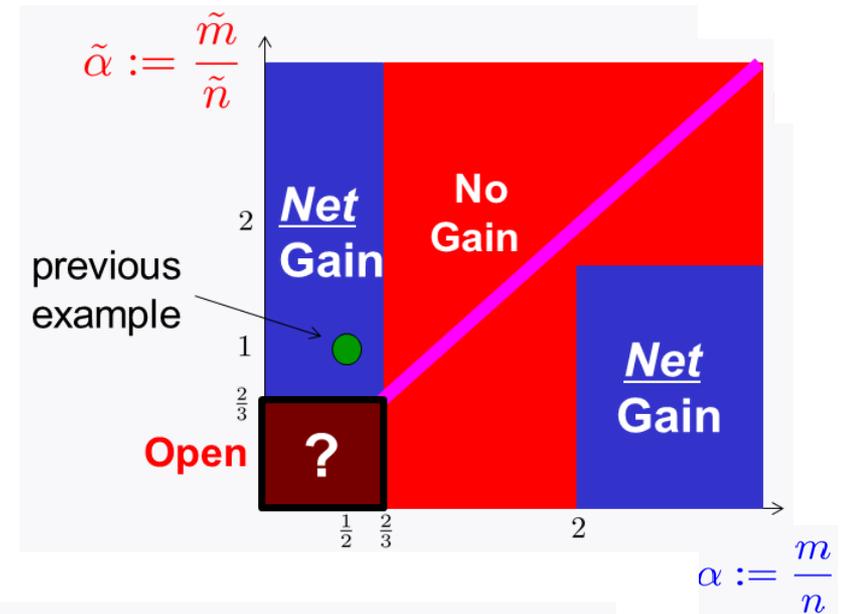
Approach: Coding theory classically assumes fixed statistic and fixed methods of coding for a given set of network and interference conditions

Payoff: Feedback in coding methods can significantly improve throughput under dynamic network and interference conditions

Feedback Coding Approach



Areas Where Improves Performance (including side information)



$$\frac{m}{n} = \frac{\log \text{INR}}{\log \text{SNR}}$$

INR = interference-to-noise ratio

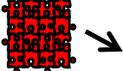


Information Systems Assessment

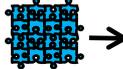
Predict system performance using mathematical invariants from measured data

Heterogeneous Information

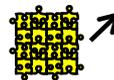
Network States
(packets, packet blocks, packet groups)



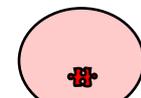
Software States
(variable, subroutine, program)



Hardware States
(register, ram, virt. mem)

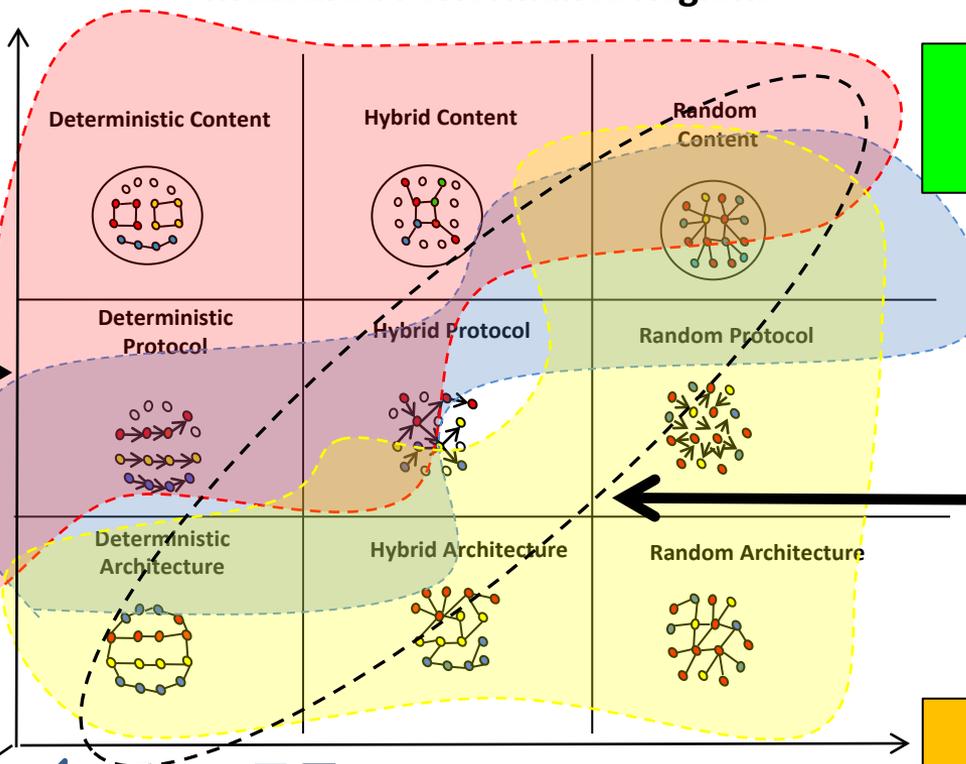


(timescale/level of abstraction)



System Measurements

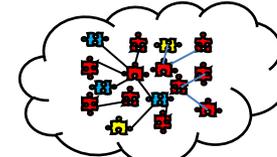
Measured Performance Regions



Less: Information Loss Under Disruption/Live
More: Latency, Resource Intensive/Safe

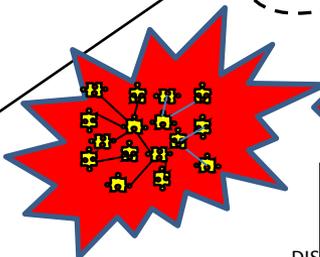


Best Integrated Performance Region

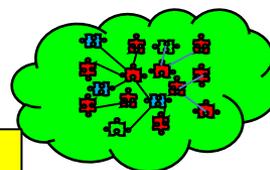


Less: Latency/Disruption Tolerant/Safe
More: Controllable/Live

Global Properties
Unstable/Un-resourced
Insecure



Invariants Predict Performance



Statistical Properties

Stable/Resourced
Secure



Hodge Theory for Invariants in Network Algorithms



ST Yau, Harvard, Ali Jadbabaie, UPenn, Fan Chung Graham, UCSD

Approach: Hodge decompositions allow natural functional invariants to be used on extremely complex structures

Payoff: Analysis of Hodge decomposition can be applied to whole classes of networks to characterize invariant parameters and predict performance.

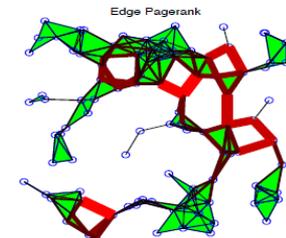
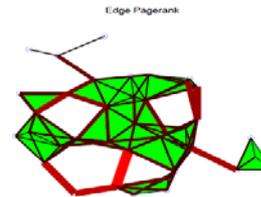
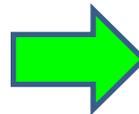
Hodge Decomposition Gives Powerful Functional Invariants

The k -Laplacian acting on $C^k(X)$ is defined by

$$\Delta_k = \partial_{k+1}\partial_{k+1}^* + \partial_k^*\partial_k$$

- ▶ $\Delta_k f = 0 \iff \partial_k f = 0$ and $\partial_{k+1}^* f = 0$
- ▶ $C^k(X) = \ker \Delta_k \oplus \text{Im}(\partial_{k+1}) \oplus \text{Im}(\partial_k^*)$ is an orthogonal decomposition called the **Hodge decomposition**.

- ▶ Write $\chi_e = h_e + g_e + c_e$
 - ▶ $g_e = \text{proj}_{\text{Im}\partial_1^*}(\chi_e)$: Gradient flow
 - ▶ $c_e = \text{proj}_{\text{Im}\partial_2}(\chi_e)$: Curl flow
 - ▶ $h_e = \text{proj}_{\ker \partial_2^* / \text{Im}\partial_1^*}(\chi_e)$: Harmonic flow



Invariant Analysis of Page Rank (Google)

$$\text{PageRank } pr(\alpha, s) = \beta s D^{-1/2} \mathcal{G}_\beta D^{1/2}, \quad \beta = 2\alpha / (1 - \alpha)$$

Invariant Analysis of Google's Page Rank Algorithm for Different Values of Beta



Topological Invariants for Model Checking Network & System Dynamics



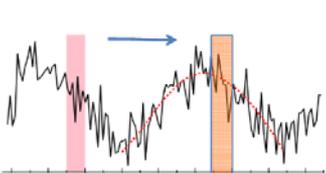
John Harer/Sayan Mukherjee Duke Konstantin Mischaikow/Rutgers, Samson Abramsky Oxford, Peter Chin Johns Hopkins

Approach: Dynamic measured data has correlated structures that are difficult to characterize by standard tools in algebraic topology such as homology. Additional features such as Conley index can augment invariants provided by algebraic topology.

Payoff: Dynamic modes of networks and networked systems can be captured by new methods in discrete Morse theory and algebraic topology to predict performance

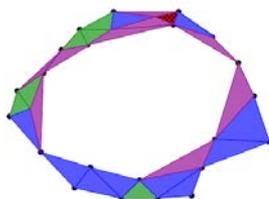
Dynamic Time Series

Initial Time Series



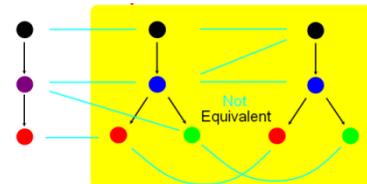
?

Geometric
Invariant
(homology)



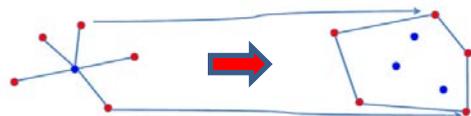
Use of Conley Index Allows Verification of Dynamics for System Assurance

Model Equivalence Checking



Time Series Data

Graphs from
Time Series



Graphs With
Invariant Cycle

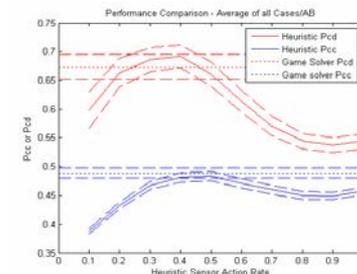
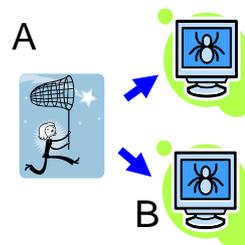
Conley Index

$$f: \mathbb{R}^n \rightarrow \mathbb{R}^n$$

Given $F: \mathcal{X} \rightarrow \mathcal{X}$ and $\mathcal{P}_0 \subset \mathcal{P}_1 \subset \mathcal{X}$ need to compute

$$f_*: H_*(|\mathcal{P}_1|/|\mathcal{P}_0|, ||\mathcal{P}_0||) \rightarrow H_*(|\mathcal{P}_1|/|\mathcal{P}_0|, ||\mathcal{P}_0||)$$

Bugs and System Instabilities Can Be Measured and Model Checked in Real Time





Categorical Invariants on Information Flows

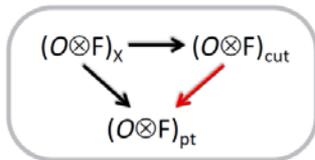
Rob Ghrist, UPenn



Approach: Dynamic network information flow can be parameterized by its max flow min cut value relative to the network topology

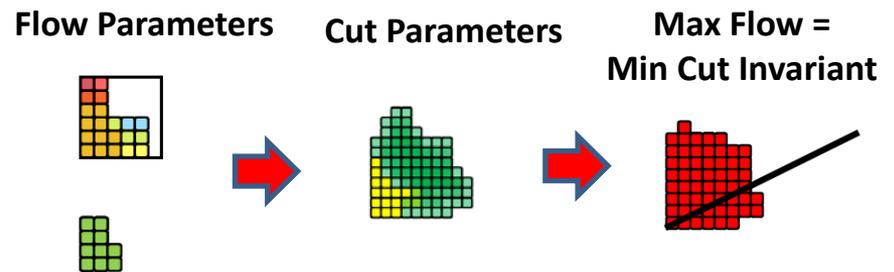
Payoff: Categories of flows can be developed using sheaf theoretic formulation for max-flow min-cut parameters to characterize and verify system performance

Sheaf Formulation For Max Flow Min Cut and Network Code

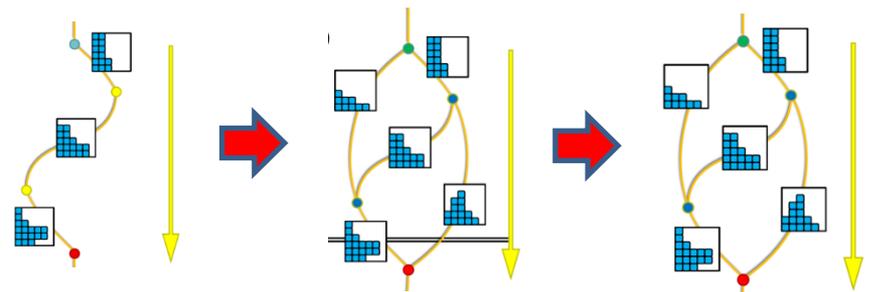


$$\begin{aligned}
 [0, \text{maxflow}] &= \bigcup_{\text{flows}} [0, \text{flowval}] \\
 &= \text{im } (O \otimes F)_X \rightarrow (O \otimes F)_{\text{pt}} \\
 &= \text{im } \lim_{\text{cuts}} (O \otimes F)_{\text{cut}} \rightarrow (O \otimes F)_{\text{pt}} \\
 &= \lim_{\text{cuts}} \text{im } (O \otimes F)_{\text{cut}} \rightarrow (O \otimes F)_{\text{pt}} \\
 &= \lim_{\text{cuts}} [0, \text{cutval}] \\
 [0, \text{mincut}] &= \bigcap_{\text{cuts}} [0, \text{cutval}]
 \end{aligned}$$

Categorical Invariants For Coded Information Flows



Corresponding Network Flow Conditions



Joint project with DARPA/DSO GRAPHS program





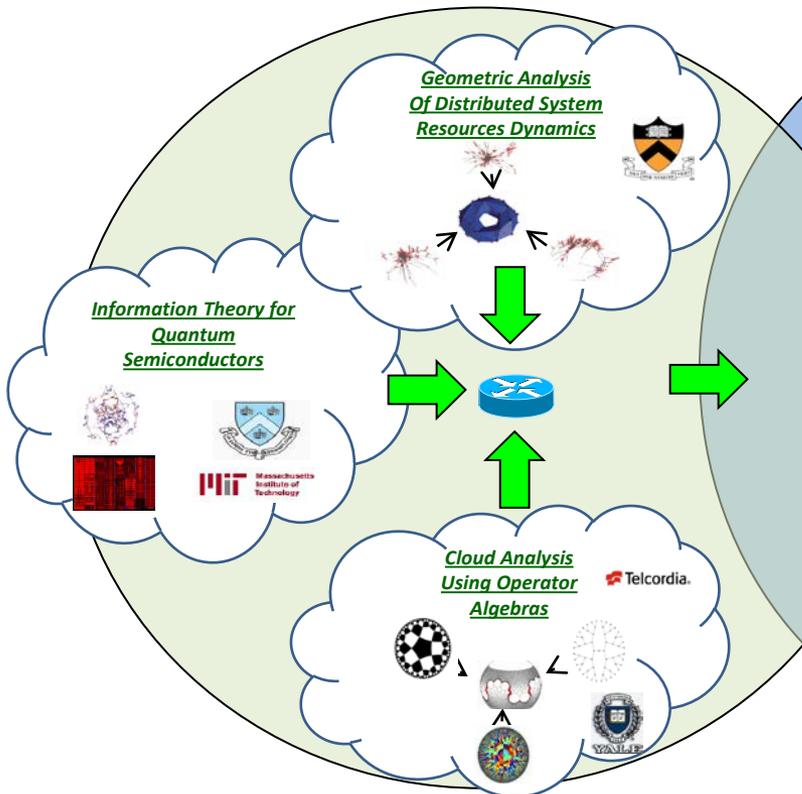
Complex Networks Transition Activities



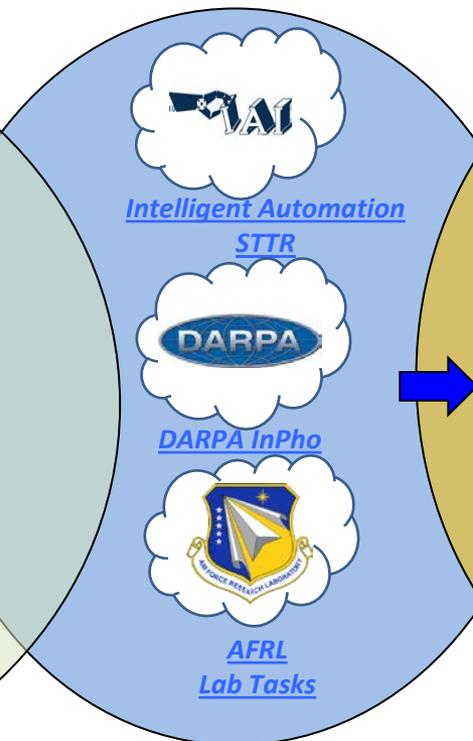
Complex Networks uses advanced mathematical analysis of information systems measurements to resource, verify, and secure distributed Air Force infrastructures

- Princeton MURI – dynamic analysis of packets for airborne network resource management
- Yale/Telcordia commercial grant – real time system security policy verification
- Columbia/MIT – information theory for new quantum semiconductors

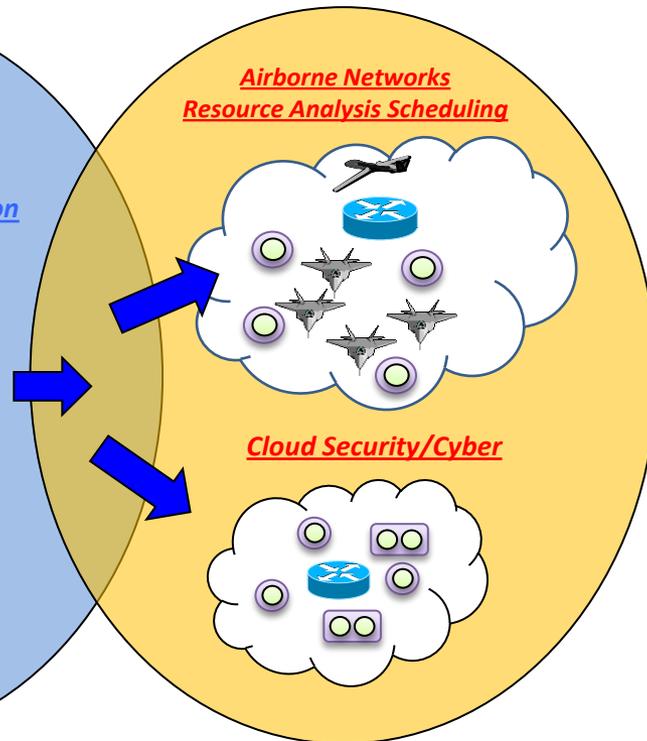
University Research



Transition Mechanisms



New Systems Components in Architecture





Space and Airborne Cognitive RF

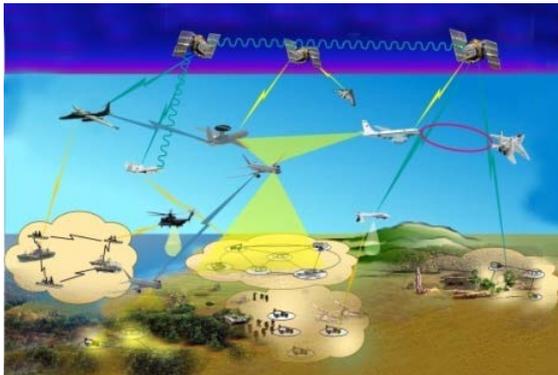


Scott Erwin, AFRL/RV, John Matyjas, AFRL/RI, Vasu Chakravarthy, AFRL/RV

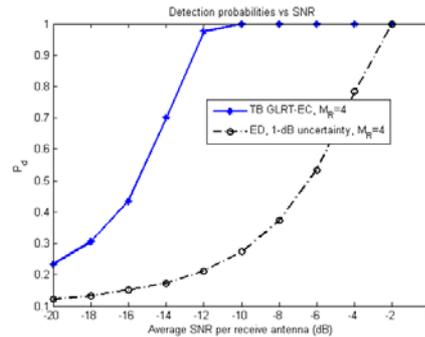
Approach: Use advanced non-parametric geometric measurement and game theoretic techniques with Generalized Likelihood ratio test to enable training on RF interference data in conjunction with advanced MIMO beam-forming techniques to remove interference

Payoff: AF will be able to conduct operations in crowded dynamic spectrum environment

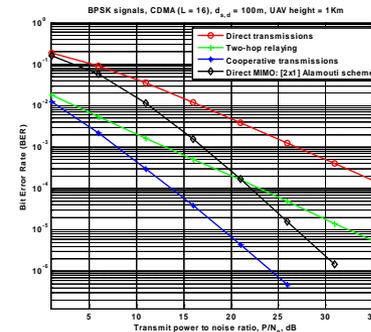
Complex RF Environment



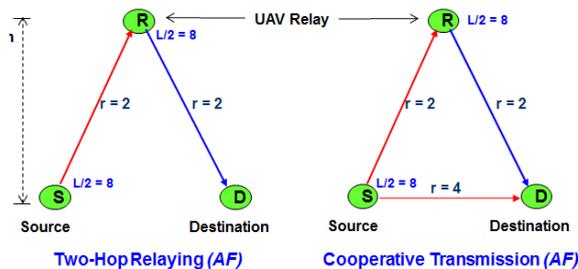
Improved Detection



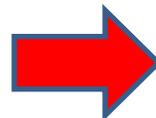
Improved Throughput



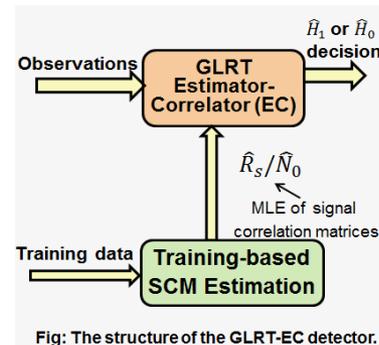
Space Time Network



Network Measurement & Invariants



Adaptive Detection



$$\Lambda_{GLRT} = \sum_{n=0}^{N_s-1} \ln \frac{P(x|H_1, \hat{R}_s)}{P(x|H_0, \hat{N}_0)} =$$

$$\sum_{n=0}^{N_s-1} x^H[n] \hat{R}_s (\hat{R}_s + \hat{N}_0 I)^{-1} x[n] / \hat{N}_0$$



Quantum Network & System Measurements



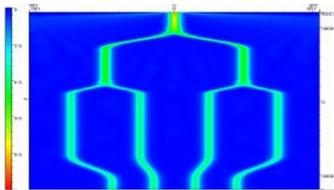
Jeff Yopez/AFRL/RD, Paul Alsing/AFRL/RI, Atilla Szep, AFRL/RY

Approach: Verification of classical vs. quantum states in a network provides a new class of measurement problems which need invariants for analysis of states of large scale quantum systems for information assurance, communication, and computing

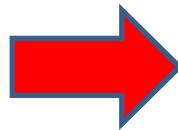
Payoff: Integrating new invariant network techniques with new quantum representations will allow a much more integrated way of analyzing large scale quantum network and computational systems

Data from Quantum Network & System Measurements

Photonic Device Measurements



Optical Measurements



Representation of Quantum Logic

$$A^{-1} \left[\frac{(e^z - 1)}{A^{-2}d} \right] \text{ (crossed) } = A \left[\text{quantum gate} \right] - A \left[\text{uncrossed} \right]$$

crossed

quantum gate

uncrossed



crossed
 $t = 0$

reconnection
 $t = 48$

uncrossed
 $t = 116$

New MURI 2012: Measurement and Verification in Quantum Information Systems



Computational Homology and Ricci Flow for Verification of Classical and Quantum States

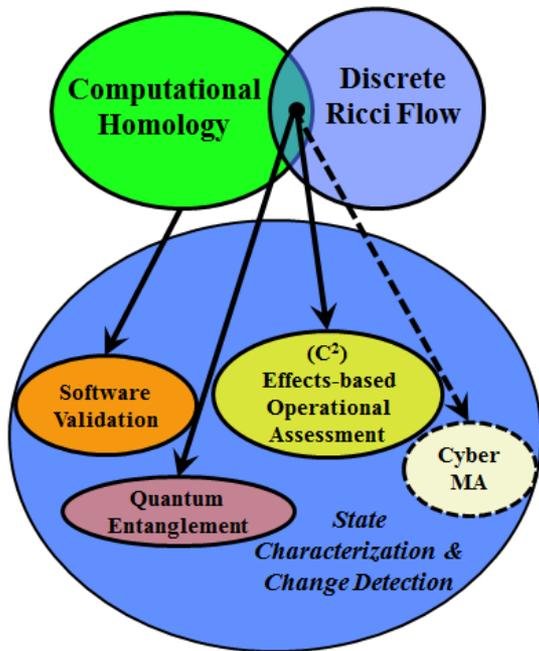


Paul Alsing/AFRL RI, Howard Bramson/Syracuse, Warner Miller, FAU

Approach: Verification of classical and quantum states in a network and system provides a new class of measurement problems which need invariants such as computational homology for analysis of states

Payoff: Integrating new invariant network techniques with new classical and quantum representations will allow a much more integrated way of analyzing & securing large scale networked and computational systems

Network Information Properties Of Curvature



Classical Information

Triangle Inequality

$$\mathcal{D}_{AB} + \mathcal{D}_{BC} \geq \mathcal{D}_{AC}$$

Polygonal Inequality

$$\mathcal{D}_{AB} + \mathcal{D}_{BC} + \dots + \mathcal{D}_{YZ} \geq \mathcal{D}_{AZ}$$

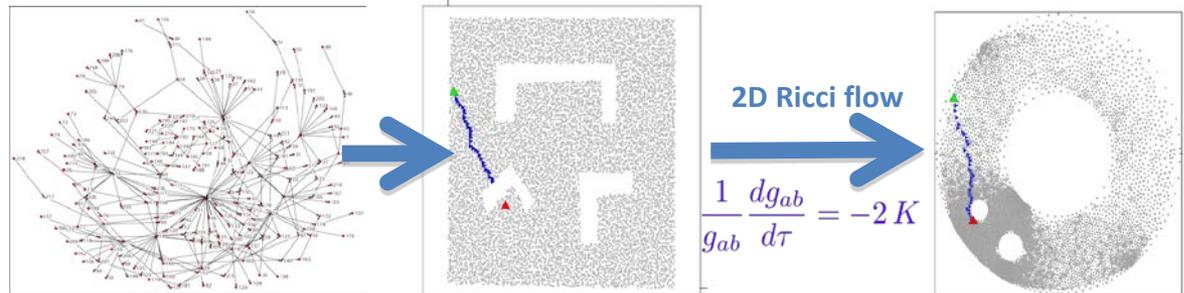
Quantum Information

Triangle, ..., Polygonal Inequalities are violated

$$|\psi\rangle = (|\uparrow_1, \downarrow_2\rangle - |\downarrow_1, \uparrow_2\rangle) / \sqrt{2}$$

$$\Rightarrow \exists \text{ no } P(A_1, B_2, C_1)$$

Network/System Decomposition





Complex Networks Invariants for Risk Assessment Measurement of Human vs. Machine Performance



Leslie Blaha, AFRL/RH

Approach: Complex Networks invariants can be used to assess risk on human vs. machine operation when faced with complex decision task.

Payoff: Detailed understanding and automation of how to trade human vs. machine performance in time critical functions such as cyber security, autonomous operation of air vehicles

Warfighter



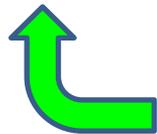
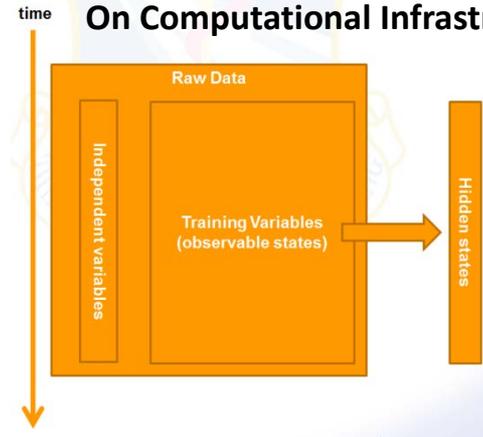
Measurement



Performance and Representation

Estimate Decision Risk
Using Complex Network Invariants

Machine Learning
On Computational Infrastructure



Human Risk
Lower

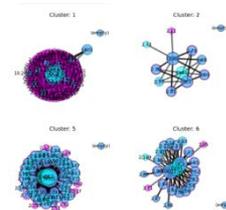
Human Behavior

t	Observed sequence	Hidden sequence
1	Walk	Sunny
2	Walk	Sunny
3	Shop	Rainy
4	Clean	Rainy
5	Shop	Rainy
6	Walk	Sunny
7	Clean	Sunny

Hidden Variable Theory



Network Representation



Machine Learning Risk
Lower



Recent Program Awards



- **Dan Speilman**
 - MacArthur Genius Award (2012)
- **Ingrid Daubechies**
 - Fellow of the American Mathematical Society 2012
 - Benjamin Franklin Institute Medal, 2012
 - Leroy Steel Prize From American Mathematical Society 2012
 - IEEE Jack Kirby Signal Processing Medal 2011
- **Robert Calderbank**
 - IEEE/Hamming Medal Winner (2012)
- **Vincent Poor**
 - National Academy of Science (2011)
- **Emmanuel Candes:**
 - Collatz Prize (Mathematics) , (ICIAM) (2011)
 - Winner, Sixth Vasil A. Popov Prize (Mathematics) ,(2010)
- **ST Yau**
 - Wolf Prize Mathematics, 2010
- **Joel Tropp:**
 - Eighth Monroe H. Martin Prize, 2011
- **Yonina Eldar**
 - IEEE Fellow 2013
- **Mung Chiang:**
 - IEEE Fellow 2012
 - IEEE Kiyo Tomiyasu Award in 2012
- **Junshan Zhang**
 - IEEE Fellow 2012



Academia/Commercial Outreach



- **Keynote Lecture, American Society of Mechanical Engineers, Complex Systems 2012**
- **Keynote Lecture, International Conference on Complex Networks, 2012**
- **Keynote Lecture, IEEE, CogSima, 2013**
- **Invited Lecture, Yale Mathematics, Anniversary of Coifman, Jones, Rokhlin Achievements**
- **Organizer: London Institute of Mathematics: Mathematics of on Statistical Verification, March 2012**
- **Organizer, OSTP Meeting on Complex Engineered Systems, 2012**
- **Invited Speaker, Allerton, IEEE Conference on Information Theory, University of Illinois 2012**
- **Invited Speaker, IDGA Big Data, Federal Meeting Washington DC, 2013**
- **Invited Speaker, Neuro-Information Processing, Lake Tahoe, 2012**
- **Invited Speaker: Dagstuhl Germany, Mathematics of Information Flow, 2012**
- **Invited Speaker: USCD Information Theory and Applications, LaJolla 2013**



Program Impact & Collaboration with Agencies



- **OSTP/NITRD – Co-Chair Large Scale Networks Working Group**
 - New national thrust – Complex Networks and Systems inspired by AFOSR program – Workshop “Complex Engineered Networks” organized by leader of AFOSR Complex Networks MURI “Information Dynamics in Networks”
- **ASDR&E**
 - Engineered Resilient Systems – Complex Networks and Foundations of Information Systems on Roadmap
- **DARPA Collaboration/joint program reviews**
 - Graphs – Mathematics of graphs and networks agent
 - Defense Science Office Mathematics Advisory Panel
 - InPho – Information in a photon/quantum network collaborative funding
 - Com-EX cognitive network program transition agent
- **IARPA – Quantum Computer Science Working Group**
- **ARL/ARO Network Science Board of Advisors**
- **NSF Future Internet, Cyber Physical Systems**



Complex Networks Trends



- **Local Network Theory**
 - Geometric and binary information coding →
 - Coding information with network performance objectives ↗
 - Integration with verification and quantum methods ↑
- **Network Management**
 - Nonparametric strategies for assessing network performance ↗
 - Distributed strategies for measuring and assessing network information transfer →
 - Sparse network management ↗
- **Global Network Theory**
 - Geometric flow analysis for prediction and management of network performance ↗
 - Global state space taxonomy and categorization ↑
- **Information Systems Research**
 - Combined network, software, and hardware analysis ↑
 - Defining correct input data for given mathematical assessment ↗
 - Invariant metrics for analysis of network performance ↑



Other Program Interactions



Cyber Operations: Joint University Center of Excellence:
“Cyber Vision 2025” – Enabling Technologies workshops
“Secure Cloud Computing” with university and AFRL/RI

Dynamics and Control : Verification and Validation of Complex Systems

Physics and Materials: New Joint MURI Topic: “Large Scale Integrated Hybrid Nanophotonics”

Socio-Cultural Analysis: Social Networks – Joint MURI Topic: “Stable Metrics for Inference in Social Networks ” – UCLA/USC/ASU

Quantum: Interaction with quantum network and quantum estimation processes through lab tasks
- Joint EOARD initiative at Cambridge

Information Fusion: Critical feature selection in sensor networks

Optimization: Competing optimization requirements.

Decision: Networks of neurons.

Biology: Systems biological processes as networks.



Transition Activities



- **AFRL**
 - AFRL/RI – Cyber Vision 2025 workshops/Illinois Center for Secure Cloud Computing/
 - AFRL/RI/RV – DARPA InPho program/DARPA Graphs program
 - AFRL/RI/RV/RH – distributed secure space communications
 - AFRL/RW/RV/RH – verification and validation of complex systems
- **STTR**
 - Intelligent Automation: Transition to ESC of Airborne Networks management – transition to Boeing for test-bed
 - Avirtek: Secure router application interface- AFRL/RI
 - Andro – Joint Spectrum Center Lockheed transition of automated spectrum management tool



Transition Activities



- Customer/Industry
 - Collaboration with ACC/GCIC, Air Force Spectrum Management Agency on JALIN ICD
 - Collaboration with Boeing, ESC, IAI for transition of coding and routing management protocols baseline CORE tools to Rome Lab for possible integration in CABLE JCTD
 - Briefing to Space Command/Peterson for potential collaboration
 - Interaction with Northrop Grumman/BACN airborne networking program for potential collaboration
- OSD
 - Complex Systems Engineering and Systems 20/20 initiative
 - Software Assurance and Security Initiative
 - Robust Command and Control Initiative
- Commercial
 - Interaction with Stanford on real time network information recovery
 - New initiatives with Akamai for content distribution analysis
 - Interaction with USFA/DHS/CISCO on router algorithm design